Disaster Risk, Social Vulnerability and Economic Development *

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Abstract

We examine the extent to which economic development reduces both a country's disaster risk and its social vulnerability to climate-related disasters. We use data from the EM-DAT database representing country-level observations over the period 1980-2007. Regressions indicate that the ability of economic development to reduce disaster risk depends on a country's income level; additional income becomes less effective in reducing disaster risk as countries become wealthier. Conditional on a disaster occurring, higher incomes generally reduce a country's social vulnerability to such disasters. We additionally find that underlying social and political structures have a significant effect on the human costs of disasters.

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1 Introduction

In recent years, economists and others have shown great interest in studying natural hazards, their economic and social impacts, and potential ways to mitigate their effects (e.g. Skidmore and Toya, 2002; Shaughnessy et al., 2010; Gassebner et al., 2010; Noy, 2009; Noy and Vu, 2010; Noy and Nualsri, 2011; Strobl, 2011; Escaleras and Register, 2010). In this study, we consider the social and economic determinants of disasters, in particular the factors that cause extreme natural events to become natural disasters.

A disproportionate share of the adverse effects of climate change are expected to be borne by the world's poor, particularly those in Africa and Asia (e.g., Battisti and Naylor, 2009; Parry et al., 2007; Tol et al., 2004; Mendelsohn et al., 2006; Allan and Soden, 2008). Additionally, recent analyses of the worldwide populations at high risk from climate change reveal a disproportionate share in low-income settings (Parry et al., 2007). For this reason, it is important to understand what factors—especially those under the influence of policy—increase or reduce a country's vulnerability to climate-related disasters.

In this paper we review a conceptual model introduced by Blaikie et al. (1994) that attempts to explain a society's vulnerability to disasters. This conceptual model, in conjunction with existing studies examining vulnerability and the determinants of disaster outcomes, provides a series of testable hypotheses that serve as the basis for our empirical exercise. We begin our empirical analysis by exploring the effects of various factors on disaster risk. Using an unbalanced cross-country panel, we estimate a series of random effects panel probit regressions to assess the effect of income, political institutions, and geography on a country's disaster risk. We then test the conceptual relationships between disaster outcomes and these social, economic, and political features to identify and measure the extent to which these factors shape social vulnerability to climate-related disasters, conditional upon a disaster occurring.

2 Conceptual Framework

Hewitt (1983) suggested that the social impacts of a disaster depend more on the underlying social structure in which a hazard occurs than the society-environmental interactions in which the hazard takes place. Under this view, vulnerability reflects disruptions to livelihoods, not merely to ecosystems or physical infrastructure (Adger, 1996, 1999; Chambers, 1997). In an attempt to explain patterns of "social vulnerability", Blaikie et al. (1994) proposed a model to track the progression of vulnerability from socio-economic, political and institutional forces into unsafe physical and social conditions leading to mortality and morbidity in the event of a natural hazard. Blaikie et al. (1994, p. 21), defines a hazard as an "extreme natural event which may affect different places singly or in combination (coastlines, hillsides, earthquake faults, savannas, rain forests, etc.) at different times (season of the year, time of day, over varying return periods, of different duration)." By this definition, many extreme natural events can be classified as natural hazards. These include earthquakes, volcanoes, landslides, droughts, floods, cyclones, and tornadoes. In contrast, a disaster occurs "when a significant number of vulnerable people experience a hazard and suffer severe damage and/or disruption of their livelihood system in such a way that recovery is unlikely without external aid" (Blaikie et al., 1994, p. 21). Blaikie et al.'s "Pressure and Release" model of disasters conceptualizes disasters as arising from the intersection of natural hazards and vulnerable societies. Where there exist both natural hazards and a vulnerable society, the risk of a disaster is significantly greater. But societies are not vulnerable merely because of their *exposure* to hazards. Exposure increases the risk of a disaster, but the vulnerability of a society is a separate force, and begins with the social, economic, and political structures and ideologies that shape the distribution of physical, human, social and political capital in a society. This view is consistent with the political economy literature focusing on incentives faced by government in disaster preparedness and response (e.g., Abney and Hill, 1966; Besley and Burgess, 2002; Khandker, 2007; Cohen and Werker, 2008). One of the social institutions that receives the most credit in these analyses is a functioning multiparty democracy. Democratic institutions generally provide transparency in government operations, a free and open discussion of policies and governmental actions without fear of threats and intimidation, an uncensored transmission of information and ideas through the media, and an electoral process which provides incentives for incumbents to do all they can to reduce the suffering of their constituents. These incentives are not typically present in dictatorial regimes or under colonialism. Political and social institutions can therefore be powerful factors influencing both pre-shock preparedness and post-shock responses.

While these root causes may be important determinants of vulnerability, they are neither necessary nor sufficient to produce a vulnerable society. Rather, underlying pressures translate these root causes into unsafe conditions (Blaikie et al., 1994). Examples of such pressures include insufficient local institutions, inadequate training and education of the populace, poor infrastructure, incomplete markets, limited press freedom, rapid population growth, rapid urbanization, onerous debt repayment schedules, and deforestation or other ecosystem damage. Blaikie et al. (1994) suggest that rapid urbanization is an especially important factor contributing to vulnerability, since rapid urbanization in many settings places immense pressure on resources that are already highly constrained. This is perhaps especially true in urban slum dwellings, where residents incur greater risks from landslides, mudslides, and floods because they live in close proximity, often in poorly constructed structures that contribute to soil erosion and the alteration of natural drainage patterns (Blaikie et al., 1994). Macroeconomic policies can also have a significant impact on vulnerability. Critics of structural adjustment programs argued that these adjustment programs, particularly first generation adjustment programs, often had unanticipated effects that amplified vulnerability (Cornia et al., 1987; Reed, 1996). Because these programs were often imposed on countries facing current account crises, one of their key ingredients was reducing public expenditures. This often required reductions in expenditures for education, health, sanitation, and infrastructure. Additionally, interest on loans diverted resources that otherwise might have been spent in ways that reduced vulnerability.

Unsafe conditions represent the most apparent manifestation of vulnerability in various forms, including fragile physical environments, fragile economies, marginalization, and insufficient public actions. There are several reasons why poorer countries might be more vulnerable to disasters than richer countries on these grounds. By and large, industrialized nations have the ability to cope with climate shocks. Municipal infrastructure (e.g., roads, bridges, water and sewer systems) is generally robust; public health infrastructure is strong (allowing developed nations to more adeptly deal with disease outbreaks, etc.); social security and other publicly provided safety nets are in place; and communication infrastructure facilitates disaster preparedness and response. The suggestion that income reduces vulnerability to climate change is not new. Schelling (1992), for example, suggested that the best defense against climate change for many countries would be continued economic development. A recent study by Wheeler (2011) supports this hypothesis, finding that an increase in per capita income lowers disaster risk, even after controlling for factors that may confound the increases in disaster reporting. This contrasts with other recent empirical applications (e.g., Kahn, 2005; Strömberg, 2007) which suggest that income may not be a significant factor in whether a country experiences a disaster.

With climate change expected to increase the frequency and intensity of climate-related hazards, the disaster pressures brought about by the exposure to these hazards are likely to increase. If this is indeed the case, then the only way to withstand the pressures that exacerbate disaster risk is to reduce social vulnerability. While there are indeed some forces in nature that are beyond any reasonable measure a society can take in avoiding them, most hazards would not be classified as catastrophic disasters. In fact, many of the damages would not occur except as a direct result of the social structures that characterize the recipient of the shock. The analysis below is organized to investigate this claim.

3 Data

The data used in our empirical analysis constitute an unbalanced panel consisting of 1,055 observations covering 103 different countries from 1980 through 2007. These data are compiled from a number of different sources. Since 1973, the Center for Research on the Epidemiology of Disasters (CRED) has been compiling a database that tracks both the human and economic tolls that have resulted from natural disasters, including historical evidence dating to the beginning of the twentieth century.[1] CRED data are compiled from many different sources, including United Nations agencies, insurance agencies, non-governmental organizations (NGOs), other research institutions and press agencies. To systematize data collection and to maintain consistency in CRED's disaster

[1]EM-DAT: The OFDA/CRED International Disaster Database - www.emdat.be - Université Catholique de Louvain - Brussels - Belgium.

database (EM-DAT), CRED defines a disaster as a "situation or event which overwhelms local capacity necessitating a request to national or international level for external assistance."[2] They use four criteria in characterizing an event as a disaster, namely that (1) ten or more people are reported killed; (2) one hundred or more people are reported affected; (3) a state of emergency is declared; or (4) a call is made for international assistance.[3] In this paper, we focus only on climate-related disasters.[4] For these, EM-DAT reports in excess of 20 million related deaths and over 6 billion persons affected between 1900 and 2010.[5] In the analysis that follows, we utilize disaster outcome data from EM-DAT, including the number of persons killed and the total number of persons affected, delimited by year, country, and disaster type. While the EM-DAT database tracks disaster outcomes back to 1900, we follow Kahn (2005) and restrict our sample to disaster outcomes from 1980 onward. Since we are primarily interested in the social outcomes of climate-related disasters, we only consider those events from which these social outcomes were reported. Deaths may be thought to demarcate more vulnerable societies from less vulnerable ones, but the numbers of affected persons are important as well, because these figures may more accurately reflect the broad impact of a disaster on a society, and they may also be more useful for policymakers in planning for both disaster preparedness and response (Guha-Sapir et al., 2004).

The number of deaths from climate-related disasters has declined steadily since the 1940s. During this time, advances in physical infrastructure and medical technology have dramatically enhanced countries' abilities to prevent deaths when climatological hazards strike. However, the total number of persons affected (but not killed) by climate-related disasters rose dramatically from the 1950s through the 1990s, and only recently has this upward trend begun to level off. Part of this dramatic increase in the number of affected persons reflects lower mortality, since some proportion of affected persons otherwise might have died if not for advancements in response and recovery. However, this fact alone fails to fully explain the scale of the difference between

[2]See http://www.emdat.be/glossary.

[3]See http://www.emdat.be/criteria-and-definition.

[4]Using EM-DAT's definitions, the climate-related disasters we consider include droughts, extreme temperatures (both extreme heat and extreme cold), floods, wet mass movements (e.g., landslides or mudslides), and storms (encompassing both tropical storms and localized convective storms).

[5]According to EM-DAT definitions, the total number of affected persons includes those injured, displaced, or otherwise needing immediate attention.

the number of deaths and the number of affected persons. Even after controlling for population growth, the number of affected persons per 1,000 population continued to increase during most of the latter half of the twentieth century, and only in the early years of the twenty-first century has this ratio fallen. Population growth alone, therefore, cannot explain the dramatic increases in affected populations that have been observed in the latter part of the twentieth century.

At least part of the explanation for this increase in the number of affected persons, therefore, must rest with an increase in the number of reported disaster events. The EM-DAT data reveal a dramatic increase in the number of reported disasters since the 1940s, which is consistent with the conjecture that changing climate conditions have increase the frequency of climate hazards. Recent studies have drawn causal linkages between anthropogenic increases in carbon concentrations and extreme climate events, including floods (e.g., Pall et al., 2011) and increased precipitation (e.g., Min et al., 2011). Additionally, evidence suggests that the intensities of storms and tropical cyclones has increased (Webster et al., 2005). The increased frequency of these climate-related hazards, therefore, lends some support to the hypothesis that a rise in the number of EM-DAT climate-related disasters might be linked to changes in underlying climatic conditions.

To allow these mortality and morbidity figures to illustrate the disaster footprint on a society, we convert the figures into deaths and affected persons per 1,000 people in the population. Using these figures as a proportion of the population is a departure from previous studies that attempt to identify economic and social correlates of disaster outcomes (e.g., Kahn, 2005; Toya and Skidmore, 2007; Strömberg, 2007), which instead control for population through the inclusion of a right-hand side covariate. By transforming the disaster outcome variables into proportional measures, we are able to isolate factors that are correlated with a large impact proportional to the population.

While it is impossible to isolate data on some of the specific root causes, pressures, and unsafe conditions identified by Blaikie et al. (1994), we introduce a number of proxy variables to capture the underlying variation in these factors. Many of these come from the World Bank's World Development Indicators. To control for the presence of marginalized ethnic groups, we use an ethnic fractionalization measure reported in Alesina et al. (2003) that captures the probability that any two individuals in the population will have different ethnic roots. Country fractionalization scores approaching zero are indicative of highly homogeneous societies, while country fractionalization scores approaching one are indicative of highly heterogeneous societies. A low degree of ethnic fractionalization is likely to result in higher degrees of marginalization for minority groups.

To control for political structures and ideologies, we use a measure of democracy and autocracy obtained from the Polity IV project.[6] This index takes on values 0–20, where higher scores represent a more democratic political structure. To proxy for access to political power, we use an index of political rights from Freedom House's Freedom in the World country rankings.[7] To control for limited access to resources and economic capital, we use a Gini coefficient measure described in Deininger and Squire (1996). Although Deininger and Squire (1996) use only high quality estimates of income inequality, Internet sources provide other, mixed quality estimates that are reported with much greater frequency. In order to include the largest amount of accessible data, we use country averages of the mixed quality Gini coefficients over the period 1980-2007.[8] ideologies, we use a measure of economic openness obtained from the Penn World Tables, v. 6.3 (Heston et al., 2009).

We additionally control for the effects of geography, using information on elevation, latitude (absolute value), and the proportion of a country's land area within 100 kilometers of an ice-free coast, obtained from the Center for International Development.[9] We account for spatial heterogeneity with regional indicator variables at the sub-continental level. The sub-continental regions include North America, Central America, Caribbean, South America, Western Europe, Former USSR, Other Europe, North Africa and the Middle East, sub-Saharan Africa, Australia and New Zealand,

4 Empirical Models and Results

Following Kahn (2005), Strömberg (2007) and Wheeler (2011), we measure the relationship between disaster risk and a range of factors associated with economic development and institutional

[6]See http://www.systemicpeace.org/polity/polity4.htm. These data were accessed on 28 January 2011.
[7]See http://www.freedomhouse.org/template.cfm?page=439. These data were accessed on 22 December 2010.
[8]See http://go.worldbank.org/UVPO9KSJJ0. These data were accessed on 28 January 2011.
[9]See http://www.cid.harvard.edu/ciddata/geographydata.htm. These data were accessed on 28 January 2011. Country latitudes are evaluated at the geographic centroid of the country. Elevation measures represent the mean elevation in meters above sea level.

characteristics. We quantify disaster risk as the probability of experiencing a climate-related disaster.[10] Modifying the empirical approach in Kahn (2005), we consider a simple random effects panel probit model of the form:

$$\text{Prob}(D_{ijt} = 1) = F(\mathit{Geography}_j, \mathit{Area}_j, \mathit{Income}_{jt}, \mathit{Institutions}_{jt}, t) \tag{1}$$

where $\text{Prob}(D_{ijt} = 1)$ is the probability that a disaster of type i will occur in country j during time period t, $\mathit{Geography}_j$ is a time-invariant vector of geographical characteristics,[11] Area_j is a time-invariant land area measure, Income_{jt} is a time-varying measure of real per capita GDP, $\mathit{Institutions}_{jt}$ is a potentially time-varying vector of characteristics regarding the underlying political and institutional structure, and t is a time trend. We use a random effects approach to estimate this model, so the link function $F(\cdot)$ is the normal cumulative distribution function.[12] We allow for a nonlinear relationship between per capita income and disaster risk by using the natural logarithm of income instead of income levels.

We begin by estimating the effects of geography, land area, income, political structures and time on the probability that country j experiences any of the climate disasters identified above. This is perhaps the broadest measure of climate-related disaster risk, since it does not distinguish among the specific types of disasters. The findings reported in column (1) of Table 1 are somewhat consistent with those of Kahn (2005) and Strömberg (2007), but are contrary with those of Wheeler (2011). While we obtain a negative coefficient for per capita GDP, this point estimate is not statistically different from zero at standard test levels, which suggests that per capita income does

[10] Wheeler (2011) uses a different definition of disaster risk, namely the log-odds ratio of the proportion of the population affected by an extreme weather event.

[11] This vector of geographic characteristics includes the absolute value of latitude, elevation, the proportion of land near an ice-free coast, and regional dummy variables.

[12] We use a random effects panel probit model for several reasons. First, and most importantly, random effects are used because the conditional likelihood approach necessary for estimation of the fixed effects model does not yield computational simplifications, as there does not exist a sufficient statistic allowing the fixed effects to be conditioned out of the log-likelihood function (Baltagi, 2001). Attempting to maximize the likelihood function over all of the parameters, including the fixed effects, in general leads to inconsistent estimates. The lack of a fixed effects estimator renders Hausman specification tests impossible. Second, even if it were possible to estimate a fixed effects probit model using a minimally sufficient statistic for the fixed effects error component, it is generally not possible to estimate the effects of any time-invariant explanatory variables in a probit setting. Third, incorporating country fixed effects would eliminate from our sample the non-trivial subset of countries for which we have only one observation. Finally, random effects are more appropriate considering the random nature of climate-related hazards.

not significantly affect a country's risk of encountering a natural disaster.

[Insert Table 1 Here]

We find that more democratic societies are no less likely to experience a climate disaster than autocratic societies. This may result from countervailing forces. In democratic societies there is typically a greater degree of transparency in governmental operations, so politicians in democratic societies have much greater accountability than politicians and bureaucrats in autocratic or totalitarian societies, and because of this increased accountability these politicians have much greater incentives to implement the necessary preparations to prevent a natural hazard from becoming a natural disaster. Democracy would therefore be expected to lower disaster risk. On the other hand, the additional transparency and better regulatory conditions found in democratic societies may improve the reporting of disasters. Kahn (2005) also suggests that the declaration of national emergencies may be influenced by political motives or may be made in repayment for electoral favors. Such political motives would not be present in autocratic political systems. This characteristic of democracy would be expected to increase the probability of a disaster being reported. The sum of these two opposing forces of democracy may ultimately result in there being no statistically significant relationship between the quality of a country's democratic institutions and its probability of experiencing a climate-related disaster.

We can assert with a high degree of certainty that geographical factors play an important role in determining a country's vulnerability. Larger countries are substantially more likely to experience disasters, as are those with a larger proportion of area within 100 km of an ice-free coast and a higher average elevation. Additionally, the point estimate associated with the time trend is highly significant, suggesting that countries have been increasingly more likely to experience (and report) climate-related disasters over time.

We next consider how these factors affect the probability of a country experiencing each of the various climate-related disasters in isolation. This may be of particular interest if the regional impacts of climate change are such that the frequency of a specific type of disaster can be expected to increase. These results are reported in columns (2)–(6) in Table 1. These results allow us to make several observations. First, while income may not significantly affect the risk of broadly-defined climate disasters, it does affect risk for several disaster types. Wealthier countries are less at risk of drought disasters but are more at risk of extreme temperature events (including cold waves, extreme weather conditions, and heat waves).

As before, geographical characteristics are important determinants of disaster risk for the various disaster types. Countries with larger land areas are more likely to suffer each of these various disaster types, while countries with a higher elevation are significantly more likely to suffer landslides and mudslides. Countries further away from the equator are less likely to experience floods and wet mass movements, but more likely to experience storms. Having a relatively large proportion of land in close proximity to the sea increases the probability that a country will experience droughts and storms, but there is no discernible effect on the probability of experiencing any of the other disaster types.

In general, these results suggest that a higher real per capita income does not lower a country's probability of experiencing a climate-related disaster, even after controlling for characteristics that are presumably the prime geographical determinants of exposure to climate-related hazards. Rather, for certain disaster types, richer countries are *more* likely to experience a reported disaster than poorer countries. However, a somewhat different story emerges when we consider the effects of income at different income levels. To see this, we classify countries in the sample as high-, middle-, and low-income based on World Bank classifications, and interact these classifications with real per capita real GDP. We then re-estimate equation 1 using the combined disaster binary outcome as the dependent variable. Incorporating the interaction terms in this fashion allows us to isolate the effect of income on reducing disaster risk at various income levels. The results from this regression are shown in column (7) of Table 1. We can compute the marginal effect of income and evaluate these marginal effects at different income levels (i.e., for different values of the income classification variables) to assess how the effect of income varies. These results suggest a nonlinearity in the effect of income on lowering disaster risk. For low income countries, an additional 1% of income lowers disaster risk by about 8%, marginally significant at test levels just outside standard levels. As per capita income levels increase, additional income has a marginally decreasing effect on lowering the probability that a country will experience a disaster (that is, the point estimates for the marginal effects become smaller as countries progress to the middle- and high-income levels) and the statistical significance of these estimated marginal effects also diminish. These results suggest that continued economic development is an important factor in reducing disaster risk, but economic development reduces disaster risk only for poor countries. Once a country attains middle-income status additional income no longer reduces disaster risk.

We compute a country-specific average predicted disaster probability using all available observations for each country and use this as a proxy for a country's underlying disaster risk. To gauge social vulnerability, we consider the number of persons killed or affected by climate-related disasters per 1,000 people in the population. Figures 1 and 2 plot disaster risk against each of these two measures of social vulnerability. From Figures 1 and 2, we see that countries with higher disaster risk also typically have a higher number of social impacts resulting from disasters. If we interpret these figures as defining the relationship between disaster risk and social vulnerability, then they also allow us to identify which countries are more vulnerable overall than they would appear to be based solely on a measure of disaster risk. The dashed lines in Figures 1 and 2 correspond to the average relationship between disaster risk and social vulnerability in the data generated by simple bivariate linear regressions. Points above this line represent countries with higher rates of social disaster outcomes than would be predicted by the average disaster risk, while points below this line represent countries with lower rates of outcomes than would be predicted by the average disaster risk.

[Insert Figure 1 Here]

[Insert Figure 2 Here]

While countries that lie below the dashed lines in Figures 1 and 2 (e.g., Canada, CAN) may be *less* socially vulnerable than would be expected given underlying disaster risk, other countries are *more* socially vulnerable than disaster risk would indicate. Many of these countries' characteristics lead to relatively low measures of disaster risk, but the social impacts of disasters are more severe than average for that particular level of disaster risk. In both figures, Swaziland (SWZ) stands out as a country significantly more socially vulnerable than would be predicted based solely on its disaster risk, though this is just one such example.

The contour lines in these figures trace out the two dimensional contours resulting from the three dimensional nonparametric kernel estimation of the bivariate densities. These contours provide a sense of the shape of the joint distribution of disaster risk and social vulnerability in our data, which also facilitates identification of countries that have disaster risks or disaster outcomes in the tails of this joint distribution. Several countries lie outside the 5% contour line, suggsting that these countries lie outside the 95% confidence interval for this joint distribution. Swaziland, Honduras (HND), Nicaragua (NIC), and Bangladesh (BGD) are in the upper tail of the joint distribution, indicating an extreme disparity between disaster risk and the social vulnerability that would be expected based on the country's underlying disaster risk. Canada, on the other hand, is in the lower tail of the joint distribution. While Canada has a high disaster risk, the social outcomes resulting from disasters are well-below what would be expected based on disaster risk alone.

In Figure 2, both China (CHN) and India (IND) appear in the upper right-hand corner, indicating both a high disaster risk and a high degree of social vulnerability. This is consistent with Wheeler (2011), who ranks China and India as the first and third most vulnerable countries to extreme weather events by 2015. However, when vulnerability is defined in terms of death rates (as in Figure 1), we find that China is less vulnerable to climate-related disasters than would be predicted based on disaster risk alone, while India is no more vulnerable than disaster risk alone would suggest. Rather, countries like Bangladesh, Nepal (NPL), the Philippines (PHL) and Vietnam (VNM) appear to stand out as especially at-risk and also highly vulnerable.

It is worth noting that 41% of Sub-Saharan African countries and 80% of South Asian countries are above the regression line in Figure 1, while 72% of of Sub-Saharan African countries and 60% of South Asian countries are above the regression line in Figure 2. This is perhaps suggestive of two stylized facts. First, while we observe a positive correlation between disaster risk and social vulnerability, these two concepts are distinct. Disaster risk is a function of, among other things, exposure to climate-related hazards. In the case of Sub-Saharan Africa, disaster risk is generally rather low. But simply because a country's geographical characteristics are such that they are not particularly prone to climate disasters does not imply that they are less vulnerable to the adverse social effects of these disasters. The characteristics of many countries in Sub-Saharan Africa are such that the probability of experiencing a disaster is low, yet the social impacts from realized disasters are large. Because many countries in Sub-Saharan Africa have larger social impacts from climate-related disasters than would be predicted solely by their disaster risk, it can reasonably be argued that Sub-Saharan Africa is particularly vulnerable to climate events, even when we consider only the impacts of *extreme* climate events and ignore increasing *mean* temperatures and precipitation levels. Second, some countries have a high degree of risk as well as a high degree of social vulnerability. South Asian countries in particular tend to fall into this category. All countries in South Asia have very high underlying disaster risk, yet the social outcomes from disasters for many South Asian countries are still greater than would be expected based on disaster risk. This suggests that perhaps South Asia is also particularly socially vulnerable to climate change, which is particularly disconcerting considering recent predictions about the potentially large impacts of climate change on these regions (e.g., Battisti and Naylor, 2009; Parry et al., 2007; Tol et al., 2004; Mendelsohn et al., 2006; Allan and Soden, 2008).

With the relationship between disaster risk and social vulnerability established, we now proceed to test the hypotheses implied by the Pressure and Release Model. In particular, we aim to examine how a country's level of economic development (measured in terms of real per capita GDP) affects social vulnerability. The model considers low income levels an unsafe condition, and therefore, poverty itself as a manifestation of vulnerability. Other studies have found that an increase in income lowers mortality and morbidity resulting from natural disasters (e.g., Kahn, 2005; Strömberg, 2007; Toya and Skidmore, 2007), although most of these other studies consider geological disasters (e.g., earthquakes, volcanoes) that we do not include here. Figure 3 plots the average number of deaths per 1,000 people against average real per capita income. This simple plot reveals no significant relationship between per capita income and the social footprint of disasters. However, a different story emerges when we consider a broader classification of disaster outcomes. Figure 4 plots the average number of persons affected per 1,000 people against average real per capita income. Here, at least so far as can be determined by a simple bivariate analysis, we find evidence of a negative correlation between per capita income and disaster outcomes, a relationship consistent with earlier empirical studies as well as the conceptual framework presented by Blaikie et al. (1994).

[Insert Figure 3 Here]

[Insert Figure 4 Here]

To proceed, we begin by separately examining each of three causal forces linked to vulnerability and then estimate a regression containing a complete set of these factors. For each of the three blocks and the complete model, we examine the effects of a vector of time-varying covariates (x'_{it}) and a vector of time-invariant covariates (z'_i) on the two measures of social vulnerability previously introduced, conditional upon a disaster occurring. The dependent variables represent totals from all climate-related disasters that a country experiences in a given year. This "punishes" countries that have multiple disasters with significant social footprints by according them a higher measure of social vulnerability. Despite a disaster occurring, the social outcome need not be a nonzero, since deaths and affected persons are mutually exclusive outcomes in the EM-DAT data. We express these outcomes as a ratio to population and use a logarithmic transformation of the indicators, adding a unit to each count of deaths and persons affected. The regressions take the general linear form:

$$\ln\left(\frac{Deaths_{it}+1}{Population_{it}/1,000}\right) = x'_{it}\beta + z'_i\gamma + \delta t + \nu_i + u_{it} \tag{2a}$$

$$\ln\left(\frac{Affected_{it}+1}{Population_{it}/1,000}\right) = x'_{it}\beta + z'_i\gamma + \delta t + \nu_i + u_{it} \tag{2b}$$

where $Deaths_{it}$ and $Affected_{it}$ are, respectively, the numbers of persons killed and affected by climate disasters in country i during year t, $Population_{it}$ is country i's population in period t, t is a time trend variable, ν_i and u_{it} are time-invariant and time-varying error components, respectively, and β, γ and δ are vectors or scalar parameters to be estimated. To estimate these parameters, we again employ a random effects panel regression.[13]

[13] Hausman tests indicate a random effects specification over a fixed effects specification. This is sensible considering

[Insert Table 2 Here]

We begin by testing the correlation between the unsafe conditions, which are presented as manifestations of vulnerability, and our measure of social vulnerability represented by the disaster outcomes. These results are presented in Table 2, columns (1) and (2). We find a generally strong correlation between these unsafe conditions and social vulnerability, with signs that would generally be expected based on the conceptual model. However, we find that different unsafe conditions are correlated with different dimensions of social vulnerability at statistically significant levels. Per capita income, for example, lowers the societal impact of disasters in terms of persons affected by disasters, but has no measurable effect on the impact in terms of deaths. The insignificance of per capita income on disaster death impacts is contrary to the findings of Strömberg (2007), Kahn (2005), and Toya and Skidmore (2007), who each find a statistically significant negative relationship between a country's level of real per capita income and death tolls from disasters. Several factors differentiate our approach from those of previous work. First, all three previous studies measure the disaster impacts in raw mortality numbers, rather than in terms of a proportion of the population. Second, the unit of analysis varies somewhat across studies. For example Strömberg (2007) uses a natural disaster as the unit of analysis, whereas we use country-year observations as the unit of analysis. Using disasters as the unit of analysis and drawing a correlation between per capita income and the disaster outcome does not account for the fact that certain countries experience multiple disasters in a given year. Hypothetically, each disaster may have a relatively low death toll, and in the full sample these death tolls may, on average, be negatively correlated with per capita income. When the death tolls are summed together during a given year, however, the societal impact of all of the disasters may be rather substantial, and the negative correlation between this social outcome and income may disappear. Our findings suggest that the observed decline in death tolls arising from natural disasters are generally independent of per capita income levels. This result is generally consistent with the bivariate relationship shown in Figure 3.

The effect of social marginalization also appears differently across the two specifications of social

the random nature of climate hazards applied to the countries in this sample. Additionally, incorporating random effects in lieu of fixed effects allows us to more easily gauge the marginal effects of time-invariant explanatory variables, such as the country average Gini coefficient.

vulnerability. A high dependency ratio is significantly correlated with a higher social impact, but this effect is not statistically different from zero when social vulnerability is measured in terms of persons affected. Since the young and the elderly may be considered particularly vulnerable members of vulnerable societies, it is not surprising that a higher relative proportion of these vulnerable segments is correlated with a higher death impact from climate disasters. The other measure of marginalization considered, ethnic fractionalization, is negatively correlated with the rate of affected persons, but not significantly correlated with death outcomes. Consistent with Escaleras and Register (2010), these findings suggest that more heterogeneous societies have lower disaster impacts than homogeneous societies. We believe it likely that, in more homogeneous societies, it is much more likely that political and economic power is concentrated in the hands of a particular ethnic majority, and it is therefore much more likely that a minority group will be marginalized and placed at risk. In very ethnically heterogeneous societies, it may be more difficult for any one ethnic group to gain a plurality in the government and marginalize other ethnic groups.

We next test the relationship between socio-economic pressures and our measures of social vulnerability. The results of these models are reported in Table 2 in columns (3) and (4). Due to a general lack of data, we are unable to control for the full range of high-level forces identified by Blaikie et al. (1994). Nevertheless, we use data for population pressures (specifically, population density, indicative of rapid urbanization, and population growth) as proxies for these broader pressures. We find very little evidence of a robust statistical relationship between these population pressures and social vulnerability. The absence of a population density effect is contrary to Kahn (2005), who finds a statistically significant negative relationship between average population density and disaster death tolls using a zero-inflated negative binomial estimation approach. One would expect that higher population concentrations—such as in densely populated urban areas—would imply a greater number of vulnerable people, which would then imply a greater disaster death toll, other things equal. Our findings suggest that once the disaster impact is framed as a proportion of the population, these population pressures have little effect on underlying social vulnerability.

In testing the root causes of social vulnerability, we again find support for the hypothesis that social and political features matter. These results are reported in columns (5) and (6) of Table 2.

Consistent with previous literature and expectations, we find that more democratic societies have lower degrees of social vulnerability.[14] While these point estimates are only marginally significant when vulnerability is framed in terms of persons affected by climate disasters, the negative effect is robust across all model specifications. We find that countries with a higher degree of average income inequality are more vulnerable in terms of disaster death rates, but no more vulnerable in terms of the rate of persons affected by climate disasters. If we interpret income inequality as indicative of unequal access to resources and power, then these results suggest that higher concentrations of wealth and power result in more vulnerable societies.

Finally, we estimate a full model that incorporates each of the variables included in the three preceding regressions. These results are reported in columns (7) and (8) of Table 2. We note that all significant point estimates from the three preceding models carry over to the full, unrestricted model, though not always with the same magnitude. The dependency ratio, for example, remains significantly and positively related to death outcomes, but the magnitude of the point estimates is significantly lower once we account for population pressures and the root causes that contribute to vulnerability. Nevertheless, incorporating all of these factors and pressures into a comprehensive model allows us to interpret with a greater degree of clarity which factors are significantly correlated with various disaster outcomes. We again find that countries with higher per capita incomes have lower levels of social vulnerability, while countries with more unequal income distributions have a higher degree of social vulnerability, at least in terms of death outcomes. Taken in tandem these results suggest that wealthier countries with a more equal distribution of resources tend to be the least socially vulnerable to climate-related disasters, while poor and very unequal societies tend to be the most vulnerable. More democratic societies are generally less socially vulnerable, though the statistical support for this claim is weak in the complete model.

The full model also suggests that greater political rights are positively correlated with our social vulnerability measures. We believe, but cannot test, that this result reflects the underlying nature of observed disaster outcomes, namely that to appear in the EM-DAT dataset, the event must be

[14] Strömberg (2007) includes both democracy and government effectiveness in his empirical analysis. He finds that countries with effective governments have lower disaster death tolls, while countries with higher degrees of democracy have higher disaster death tolls.

reported. As such, the positive correlation could indicate that countries with more political rights may be more likely to report disaster mortality and morbidity, or that their citizens demand greater response. This would then be reflected in higher disaster impact reporting.

Interestingly, we find that countries that are more open to international trade have higher levels of social vulnerability. This result, which is robust across model specifications and under various restrictions, is contrary to Toya and Skidmore (2007), who find that openness to trade reduces natural disaster death tolls.[15] This is also seemingly in contradiction to the conventional wisdom regarding the benefits of trade liberalization. A large body of research suggests that trade liberalization promotes economic growth and reduced poverty (see, for example Dollar, 1992; Ben-David, 1993; Sachs and Warner, 1995; Frankel and Romer, 1999), although critics of the trade and growth literature (e.g., Rodriguez and Rodrik, 2001) have often suggested that trade does not necessarily promote growth, but rather that other macroeconomic policies which coincide with trade liberalization conflate the interpretation of trade effects. One reason why increased openness to trade may not necessarily contribute to growth in per capita incomes is that such increased openness to trade is often accomplished through the exportation of primary commodities, including natural resources. While this may contribute to an increase in the trade share of GDP, it does not necessarily translate into increases in per capita income. If the increased social outcomes that were attributed to general openness to trade were in fact due to resource dependence, then one would expect the effect of openness on social vulnerability to either lose statistical significance or change signs when one controls for resource dependence. However, we find no support for this hypothesis. Even after controlling for resource dependence, we find that openness to trade is still positively correlated with social disaster outcomes.[16]

As an additional explanation, we note that many poor countries received concessionary loans from the World Bank and the International Monetary Fund (IMF) during the 1980s and 1990s.

[15] When we, like Toya and Skidmore (2007), use raw disaster outcome numbers (instead of rates), we find a statistically significant negative relationship between openness to trade and these social outcomes. This suggests that openness to trade is correlated with lower raw tolls in countries, but positively correlated with the societal impact of disasters.

[16] These side regressions are not reported here. To control for resource dependence, we consider agricultural raw material exports, fuel exports, and ore and mineral exports as a share of GDP, as reported in the World Development Indicators.

Many of these were coordinated under the Fund's Structural Adjustment Facility (SAF) or Enhanced Structural Adjustment Facility (ESAF). These concessionary loans often carried conditions aimed at strengthening the recipient countries' external balances and macroeconomic stability. Policy prescriptions for these countries included fiscal discipline, tax reform, interest rate liberalization, privatization, deregulation, and trade liberalization specifically aimed at export promotion. One of the unintended consequences of these policies was a reduction in health and education expenditures (coinciding with a general reduction in public expenditures) and an increase in unemployment (due to the privatization of state-owned enterprises), both of which can contribute to higher social vulnerability. But as a result of trade liberalization, many of these recipient countries also had significant increases in trade volumes and openness to trade measures, which could generate a positive correlation between openness to trade and social disaster impacts. To test this hypothesis, we interact a country's openness to trade with a binary variable equal to one in the year a country received an IMF SAF/ESAF loan and all subsequent years (to allow for the persistent effects of these policies). We find that under both specifications for the dependent variable, the structural adjustment effect does not significantly alter disaster outcomes, and the positive relationship between openness and disaster outcomes remains.

We conclude that this correlation reflects a more general relationship between openness and engagement with—and perhaps dependence on—the international community. Countries that have a high degree of openness to trade are less self-sufficient and may be more likely to welcome international assistance, including the involvement of international humanitarian and disaster relief organizations. This is somewhat consistent with previous research. For example, Strömberg (2007) finds that greater trade volumes are positively correlated with both the provision of humanitarian assistance and the amount of assistance that is provided. Since one criterion CRED uses in defining events as disasters is whether a call for international assistance is made, general openness may lead to an increased frequency of reported disasters and disaster outcomes.

5 Concluding Remarks

In this paper we have examined factors correlated with climate-related disaster risk and social vulnerability. Consistent with previous research, we find that, in general, wealthier countries are no less likely to experience a climate-related disaster than poor countries, once we control for geographical characteristics and regional dummy variables that can be expected to capture exogenous exposure to climate hazards. However, when we examine the effects of income at different income levels, we find that a proportional increase in income reduces disaster risk more for poor countries than for rich countries.

Using predicted probabilities from random effects panel probit regressions, we theorize a linear relationship between disaster risk and social vulnerability, where social vulnerability is understood as the proportion of population killed or otherwise affected by climate-related disasters. Simple bivariate analysis reveals that, on average, countries with higher average disaster risk are more socially vulnerable to climate-related disasters. Many countries in Sub-Saharan Africa and South Asia are more socially vulnerable to climate disasters than one would otherwise predict based solely on underlying risk of disaster. Countries in Sub-Saharan Africa do not, in general, have a very high underlying disaster risk. Nevertheless, when disasters strike, impacts resulting from these disasters can be severe. Countries in South Asia, on the other hand, have very high disaster risk. Yet despite this high disaster risk, the social impacts resulting from these disasters are generally much higher than one would expect based solely on higher underlying risks.

The Pressure and Release model, first introduced in Blaikie et al. (1994), makes some rather unambiguous claims regarding the progression of social vulnerability. The model suggests that root causes and pressures lead people to live or work in unsafe conditions. These unsafe conditions are manifestations of vulnerability, and are generally precipitated by underlying features of the society. Using random effects panel data methods, we test the hypotheses implied by the model, and find general support for its predictions. Generally speaking, wealthier countries are less vulnerable to climate disasters than poorer countries. But while wealthier countries are typically less vulnerable to climate disasters, countries with high income inequality are more vulnerable. Since income inequality is also likely indicative of an unequal distribution of social and political power and resources, a more unequal income distribution can contribute to the marginalization of segments of the population. Other factors that capture a degree of social marginalization, such as the dependency ratio and ethnic fractionalization, also suggest that countries with marginalized populations are more vulnerable to climate disasters. These results suggest that continued economic development and institutional strengthening is a meaningful strategy for poor countries to follow in protecting themselves against disaster risk.

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Table 1: Probability of Experiencing Various Climate-Related Disasters—Random Effects Panel Probit Estimation

	(1) Any Disaster	(2) Drought	(3) Extreme Temperature	(4) Flood	(5) Wet Mass Movement	(6) Storm	(7) Any Disaster
Constant	-2.689^{***}	0.345	-5.573^{***}	-2.293^{***}	-3.592^{***}	-2.684^{***}	−1.368
	(−4.150)	(0.560)	(−6.496)	(−4.498)	(−4.944)	(−3.644)	(−1.612)
ln(Real Per Capita GDP)	0.021	-0.313^{***}	0.188	0.020	0.123	−0.104	−0.227
	(0.191)	(−3.089)	(1.350)	(0.230)	(1.013)	(−0.764)	(−1.459)
ln(Real Per Capita GDP)× High							0.190^{**}
							(2.373)
ln(Real Per Capita GDP)× Middle							0.082
							(1.531)
Polity	−0.017	0.002	−0.007	$-0.033*$	$0.041*$	0.011	−0.019
	(−0.860)	(0.081)	(−0.236)	(−1.890)	(1.709)	(0.528)	(−1.013)
Political Rights	0.007	0.019	0.062	$0.097*$	−0.007	−0.024	0.009
	(0.108)	(0.254)	(0.663)	(1.664)	(−0.088)	(−0.331)	(0.136)
Elevation	$0.310*$	0.191	−0.271	0.153	0.763^{***}	0.033	0.340^{**}
	(1.804)	(1.428)	(−1.306)	(1.136)	(4.111)	(0.145)	(2.048)
Abs. Value of Latitude	−0.006	−0.000	−0.001	-0.021^{**}	-0.036^{***}	0.027^{**}	−0.011
	(−0.510)	(−0.020)	(−0.097)	(−2.412)	(−3.026)	(1.974)	(−0.981)
Area Near Ice-Free Coast	0.823^{**}	0.570	−0.299	0.071	0.084	0.994^{**}	0.811^{**}
	(2.170)	(1.619)	(−0.637)	(0.233)	(0.197)	(2.128)	(2.227)
ln(Land Area)	0.396^{***}	0.135^{**}	0.333^{***}	0.380^{***}	0.379^{***}	0.244^{***}	0.419^{***}
	(5.328)	(2.233)	(3.807)	(6.400)	(4.569)	(2.707)	(5.750)
Time Trend	0.077^{***}	0.007	0.061^{***}	0.061^{***}	0.011	0.037^{***}	0.079^{***}
	(8.607)	(0.660)	(4.697)	(7.773)	(1.068)	(4.207)	(8.799)
# Obs	1,055	932	1,023	1,055	1,041	1,055	1,055
# Groups	103	89	99	103	101	103	103
Log-Likelihood	−490.490	−231.395	−177.694	−511.666	−241.740	−413.400	−487.596

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Note: Z-statistics in parentheses. Each of these regressions contain time-invariant sub-continental dummy variables to control for geographic heterogeneity. There are no Caribbean country-year observations in our sample for which a drought or an extreme temperature disaster was reported. Inclusion of a Caribbean regional dummy would perfectly predict a 0 entry for the binary dependent variable in the regressions reported in columns (2) and (3). Observations for Caribbean countries were dropped from the sample prior to estimating these models. Similarly, there are no North American country-year observations in our sample for which a drought or a wet mass movement disasters was reported. North American countries were dropped from the sample prior to estimating the models in column (2) and (5), respectively. Finally, there were no Other European country-year observations in our sample for which a drought was reported. These observations were dropped from the sample prior to estimating the model in column (2). These changes to the sample size are reflected in the number of observations and the number of groups for these models.

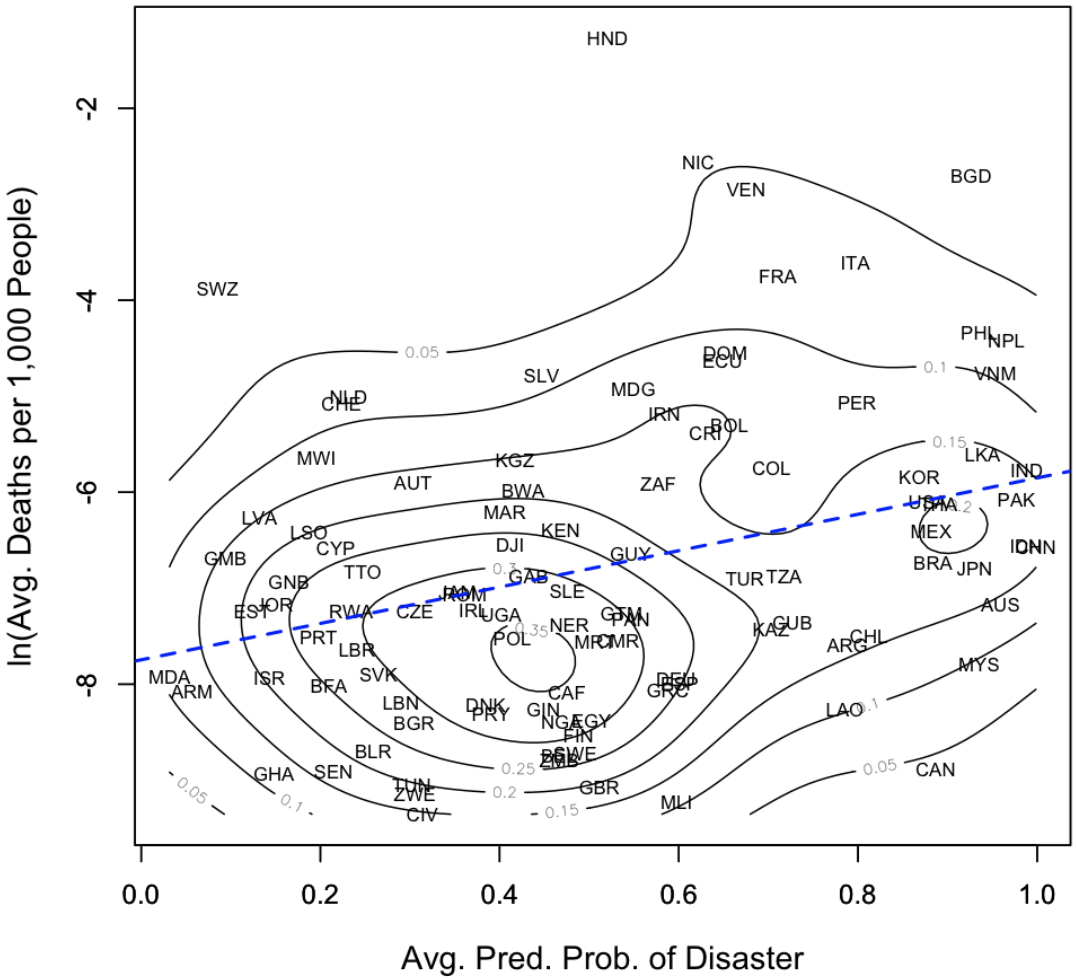
Table 2: Disaster Outcomes—Random Effects Panel Regressions

	Unsafe Conditions		Dynamic Pressures		Root Causes		Full Pressure and Release Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln\left(\frac{\text{Deaths}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Affected}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Deaths}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Affected}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Deaths}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Affected}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Deaths}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Affected}}{\text{Pop}}\right)$
Constant	−14.755***	0.596	−6.413***	−0.421	−7.897***	−1.573	−14.796***	2.194
	(−3.808)	(0.079)	(−11.398)	(−0.386)	(−8.852)	(−0.950)	(−3.925)	(0.301)
ln(Real Per Capita GDP)	−0.160	−0.706**					−0.178	−0.695**
	(−0.866)	(−2.373)					(−0.897)	(−2.146)
ln(Telephones per 1,000 people)	0.176	−0.186					0.051	−0.267
	(1.312)	(−0.561)					(0.346)	(−0.676)
ln(Dependency Ratio)	2.153***	0.603					1.603**	0.239
	(3.022)	(0.397)					(2.395)	(0.156)
ln(Physicians per 1,000 people)	−0.035	−0.373***					−0.012	−0.383**
	(−0.404)	(−2.597)					(−0.120)	(−2.191)
Ethnic Fractionalization	−0.667	−3.531***					−0.371	−3.326***
	(−1.117)	(−3.818)					(−0.613)	(−3.507)
ln(Population Growth)			−0.000	−0.084			0.048	−0.074
			(−0.003)	(−0.363)			(0.632)	(−0.312)
ln(Population Density)			0.143	−0.244			0.199	−0.166
			(1.277)	(−1.173)			(1.492)	(−0.961)
Polity					−0.024	−0.090	−0.017	−0.062
					(−0.966)	(−1.576)	(−0.668)	(−1.320)
Political Rights					0.099	0.166	0.109	0.241
					(1.028)	(0.860)	(1.023)	(1.299)
Openness to Trade					0.005**	0.013**	0.006**	0.012**
					(2.000)	(2.316)	(2.405)	(2.413)
Avg. Gini Coefficient					0.032**	−0.004	0.026*	−0.010
					(2.331)	(−0.149)	(1.953)	(−0.412)
# Obs	577	577	577	577	577	577	577	577
# Groups	95	95	95	95	95	95	95	95
R^2: Within	0.11	0.12	0.10	0.12	0.09	0.11	0.10	0.12
R^2: Between	0.17	0.68	0.17	0.59	0.23	0.65	0.27	0.73
R^2: Overall	0.19	0.44	0.16	0.40	0.19	0.41	0.22	0.45

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

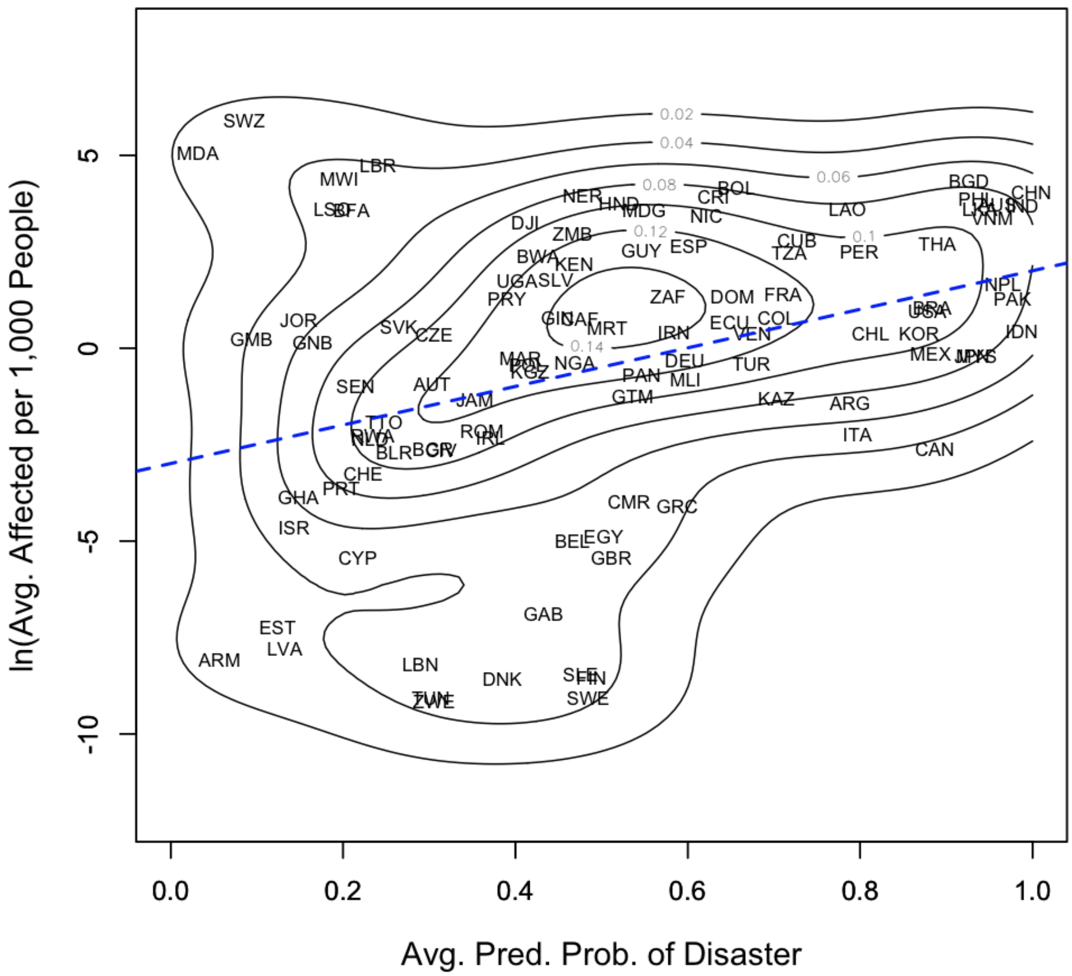
Note: Z-statistics in parentheses. For each regression, the dependent variable is computed per 1,000 people in the population. Each of these regressions contain variables to control for the number of droughts, extreme temperature disasters, floods, wet mass movements, and storms experienced in a country-year observation, as well as time-invariant regional dummy variables. Estimates have been obtained using the Swamy-Arora method for estimating variance components in unbalanced panels. Standard errors have been adjusted to control for within-country clustering and serial correlation as well as cross-sectional heteroskedasticity.

Figure 1: Average Predicted Probability of Experiencing a Climate-Related Disaster and Average Number of Deaths



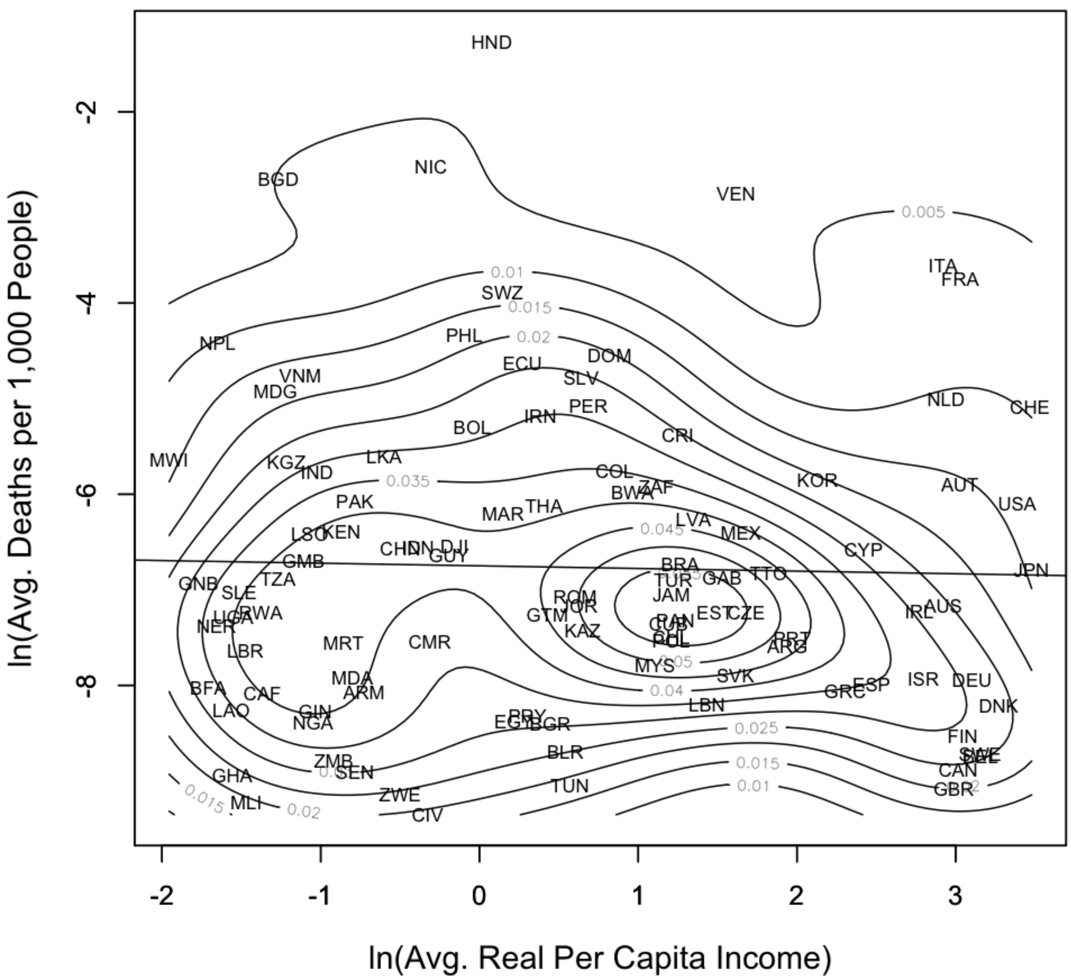
Note: Contour lines represent the two-dimensional density contours from nonparametric kernel density estimation of the joint distribution using an axis-aligned bivariate normal kernel.

Figure 2: Average Predicted Probability of Experiencing a Climate-Related Disaster and Average Number of Persons Affected



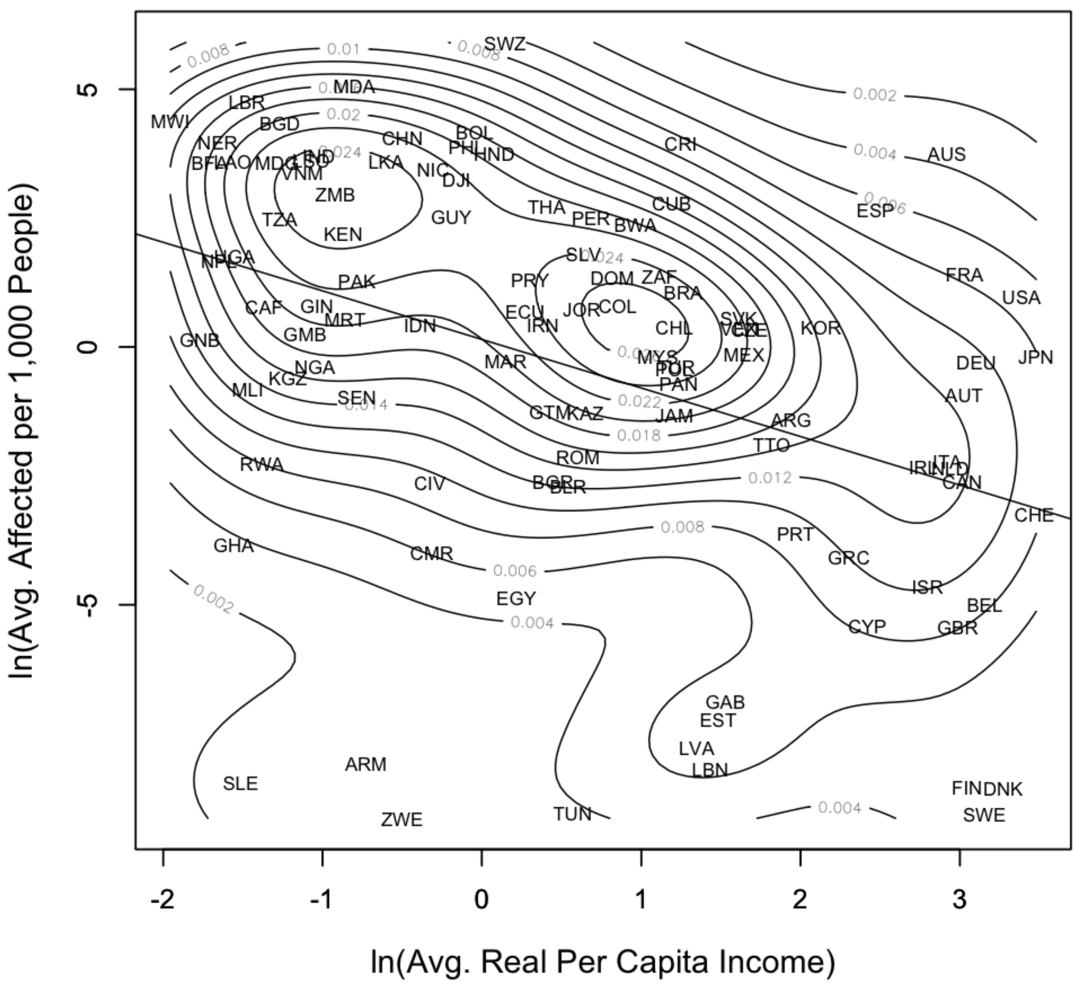
Note: Contour lines represent the two-dimensional density contours from nonparametric kernel density estimation of the joint distribution using an axis-aligned bivariate normal kernel.

Figure 3: Average Rate of Climate-Related Deaths and Average Real Per Capita GDP



Note: Contour lines represent the two-dimensional density contours from nonparametric kernel density estimation of the joint distribution using an axis-aligned bivariate normal kernel.

Figure 4: Average Rate of Persons Affected by Climate-Related Disasters and Average Real Per Capita GDP



Note: Contour lines represent the two-dimensional density contours from nonparametric kernel density estimation of the joint distribution using an axis-aligned bivariate normal kernel.